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Did the Great Recession force female spouses to work?

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Did the Great Recession force female spouses to work? Added Worker Effect in the U.S. labor market in 2008

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Abstract

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The paper is an empirical labor economics study on the Added Worker Effect (AWE) of the 2008 U.S. labor market during the period so-called "Great Recession". As the scale of the Great Recession influenced not only the financial market, but also the real market, the U.S. labor market in 2008 is an appropriate period for analyzing how members of households responded to negative economic shock on a labor supply level.

In this study, we investigate whether female spouses increased quantity of labor supply to compensate for lost earnings in households where male breadwinners became unemployed during the Great Recession. We derive the equation for empirical analysis from the household lifecycle labor supply model by using first order conditions of utility optimization, and estimate the equation using Panel Study of Income Dynamics (PSID) dataset. By estimating data applying three econometric techniques on panel data analysis, signs of estimated coefficients in all samples support our AWE hypothesis. The size of coefficients indicating AWE are especially larger in ethnic and housing asset sub-sample minority groups who most intensely felt the effects of the Great Recession. In these groups, we find that female spouses' leisure consumption decrease to 0.037-0.048 hours per week. Compared to previous studies on this topic, the size and significance of our study is much greater, implying that some groups of female spouses in the Great Recession could have increased their labor market working hour to compensate for income loss from their male breadwinner's job displacement.

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Keywords: Labor market in the Great Recession, Female Labor Supply, Added Worker Effect, Panel Study of Income Dynamics (PSID)

JEL Classification: D13, D91, E24, J14, J22

Contents

"Labor Market conditions have deteriorated dramatically since the start of the Great Recession in late 2007..." [1]

"No matter what indicator of labor market activity we consider, the deterioration of labor market conditions during this recession is the worst on record since the late 1940s." [2]

1 Introduction

The global financial crisis so called 'The Great Recession', started in the U.S. in 2008 and has had a dramatic influence not only on the financial sector but also on real sectors. The labor market was not an exception. Some studies on the effects on the labor market environment following the crisis (Elsby, Hobijn, and Sahin (2010), Katz (2010), Farber (2011)) commonly point out that labor market conditions for workers have severely worsened. After the crisis, the unemployment rate soared and unemployment duration became much longer. (See section 2.1) Following these labor market conditions changes, we can infer that households with unexpected unemployment shock (and ensuing negative income shock) would also change their household consumption during the recession time.

Suppose there is a household whose family head has lost her job unexpectedly and involuntarily in the recession period. How would the lifetime consumption path of the family have changed? According to the basic idea of M.Friedman's well-known 'Permanent income hypothesis', someone's per-period consumption is determined by her expected lifetime income, and her consumption path smoothes by saving and borrowing between present and future income. Thus, the household would attempt to ease their consumption by 'saving and borrowing' via the capital market. However, how could households attempt to ease their lifetime consumption path when their ability of intertemporal income saving and borrowing is not complete? One possible way is to increase the quantity of secondary worker's labor supply (i.e intra-household labor

[1] Katz (2010)

[2] Elsby, Hobijn, and Sahin (2010)

supply adjustment among household members), earning additional labor incomes to compensate the income loss from family head's unemployment. This phenomenon is called 'Added Worker Effect (henceforth AWE)' in the labor economics tradition. [3]

'The Great Recession' and 'Added Worker Effect' are two key terms explored in this article. More specifically, I tried to find empirical evidence of AWE during the U.S. labor market in the Great Recession period. Put simply, when some households in the Great Recession are economically injured by their head's involuntary unemployment and they face constraints on borrowing via the capital market, do they try to ease their comsumption path by other household members' additional work? It is an empirical question, asking for data analysis.

When the household's head loses her job and the family income decreases, the standard static family labor consumption choice model in labor economics literature tells us that 'income effect' and 'cross-substitution effect between household members' would determine the change of a secondary worker's working hours. If the secondary worker (in this article, a wife in the family)'s leisure time is a normal good, the household's income loss due to the head's unemployment would decrease her leisure consumption and increase labor supply (Income effect). Also, if the leisure time of the head and wife can be partially substituted for household production, secondary workers' labor supply can be increased, as head's leisure increase from her unemployment would decrease the opportunity cost of secondary workers' labor market work (Cross-Substitution effect).

However, when looking at the dynamic family labor supply model under the 'ideal' economy [4], it holds that theoretically there should be no AWE. Under the complete capital market where agents can freely trade Arrow-Debreu assets, households would alleviate economic shocks not by increasing secondary workers' labor supply in the labor market, but by borrowing from the capital market. Thus, no additional labor supply would be necessary.

[3]The idea of Added Worker Effect explained in the body text is on the 'intensive margin' side, focusing on the behavioral change of secondary workers' labor supply, who have already worked in the labor market.

[4]'ideal' means economy without information asymmetry and complete capital market, that there exist Arrow-Debreu assets for all possible contingencies.

Nevertheless, previous studies have shown that there can be a small but significant AWE when the 'ideal economy' assumption is no longer valid. That is, when there are borrowing constraints limiting the ability of intertemporal capital adjustment, households experiencing head's unemployment can not fully insure income loss through the capital market. (Lundberg (1985)) Or, if households' prospects for future lifetime income process is altered after the head's unemployment, there could be AWE even though the capital market is complete (Dynarski and Sheffrin (1987)). In the real U.S economy in 2008-2009, the Great Recession which stemmed from financial instability weakened households' capital borrowing availability (especially for minorities who are vulnerable to economic shocks). Furthermore, there seemed to be a high probability that the long term phase of the recession would change each unemployed households' expectation of future lifetime earnings. Based on these economic backgrounds, AWE might have occurred in the U.S labor market in 2008-2009.

Compared to previous studies on AWE, our study is unique in that the remarkable economic event ("The Great Recession") is used to investigate the existence of AWE, especially for some minority groups who are insufficiently prepared for economic shocks. In a methodological respect, this study uses the household life-cycle labor supply model to observe intensive margin aspect of AWE.

2 Literature

In the literature review section, I will make two subsections that each are closely related to the research topic. The first is about the U.S labor market condition during the Great Recession especially investigating how the recession worsened labor market environment. The other is concerning how the female spousal labor supply can be used to make up income loss from the household head's unemployment.

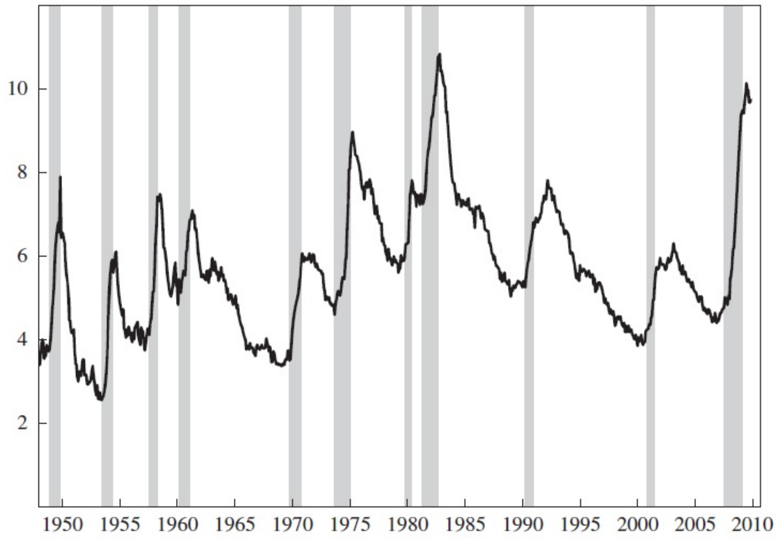
2.1 The U.S labor market in the Great Recession

As the Great Recession was a fairly recent event in the U.S economy, research on U.S labor market environment during the recession are not yet sufficient. In this section, two recent studies on labor market change during the Great Recession, by Elsby, Hobijn, and Sahin (2010) and Farber (2011), will be briefly reviewed to observe the big picture of the labor market environment in the Great Recession.

Analyzing several economic indicators of the U.S labor market, Elsby, Hobijn, and Sahin (2010) found that the labor market after the Great Recession represented the deepest downturn in the post World War II era. According to their research, the labor market in the Great Recession had shown strikingly similar patterns to previous economic downturns like the Great Depression in 1930's or the Energy Crisis depression in early 1980's. Unemployment rates reached postwar highs (Figure 1, describing unemployment rate from CPS data, revealed that unemployment rate soared to 5.7% at the beginning of the Great Recession time.) and the labor force participation rate dramatically dropped. Among several demographic groups, minorities such as less-educated, male, young, non-white worker groups were hit hardest in the recession. When analyzing the reason for unemployment in the Great Recession time, the relative portion of layoffs has increased while the portion of labor force entry has decreased. [5] Also, Elsby, Hobijn, and Sahin (2010) convincingly showed that matching efficiency between employers and unemployed declined during the recession. Unemployed workers in the Great Recession were less successful in finding new jobs. By utilizing the historical Beveridge Curve, the authors claim that the unemployment rate was higher than historical trends would indicate. Weakened matching efficiency increased the size of long-term unemployment, and decreased the transition probability of long-term unemployment to re-employment.

In Farber (2011) , the author focused on job loss in the Great Recession using the 2010 wave of Displaced Worker Survey(DWS), a sub-data unit of the Current Population Survey (CPS). Consistent with Elsby, Hobijn, and Sahin (2010), Farber (2011) documented that the unemploy-

[5] see Figure 9 in Elsby et al(2010).



Source: Bureau of Labor Statistics data.
a. Monthly data, seasonally adjusted. Shading indicates recessions.

Figure 1: Unemployment rate 1948-2010, from (Elsby, Hobijn, and Sahin, 2010)

ment rate was exceptionally high and unemployment durations were quite long during the Great Recession. (See figure 2 in Farber (2011), which presents the time trend of unemployment duration.) According to Farber (2011), less than 50% of job losers in the Great Recession succeeded in finding new jobs until January 2010, and others who failed to get a job suffered longer spells of unemployment.

From these literatures, we can infer that the labor market in the Great Recession was devastated and displaced households faced severe economic trouble, especially income loss. In the permanent income hypothesis, households try to smooth their life-time consumption path by adjusting for life-time income. To ensure one's consumption lifetime path is involatile, displaced households should find some alternative financial means to make up for their labor income loss. In a large financial crisis like the Great Recession, however, displaced households would have a hard time raising money due to obstacles to borrowing money in the finance market. Therefore, it is natural to conject that households will depend on other means of income, such as additional worker's labor to compensate income loss.

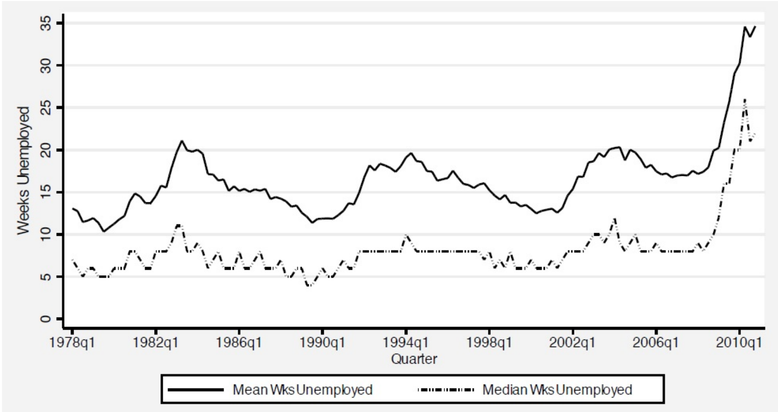


Figure 2: Duration of Unemployment, from (Farber, 2011)

2.2 Female labor supply in the household

Female spousal labor supply as a self-insurance for household income losses from the head's unemployment has been empirically studied in several studies. Broadly, there are two approaches to this issue. The first approach focuses on extensive margins, investigating whether exogenous economic shocks on the household affect other members' (who are in non-labor force) decision on whether to enter the labor market. Studies based on this approach usually use the binary response model (logit or probit) to find the causation between exogenous economic shocks on the labor market entry decision. The other approach is based on intensive margins, considering how '(labor market) existing workers' change their working behavior. Most reduced form studies like Spletzer (1997), Skoufias and Parker (2006), and Lee (2013) follow the former approach, while studies based on the lifecycle model like Stephens (2002) and Ahn (2009) follow the latter approach. Our study is in the latter approach tradition.

Stephens (2002) has investigated added worker effect of displaced workers in a household life-cycle labor supply framework using PSID (1968−1992) data. Dynamic labor-supply estimation literature from MaCurdy (1981) provides a labor supply empirical equation. As summarized in Table 1, Stephens' primary findings show that there had been a slightly significant added-worker effect in the displaced worker's households. Also, the magnitude of a spouse's labor supply increase was larger in the post-displaced time, rather than that of prior-displaced time. From the study, we can infer that female spouses in households whose head was displaced from work would attempt to compensate labor income losses after the displacement event happened, rather than precautionarily prevent labor income loss before the job loss actually occurred. Furthermore, after displacement occurs, the wife's additional labor supply became larger in $t+2$ than $t+1$. As there have been some labor market frictions and crowding-out effects from unemployment insurance benefits, the author claimed that it takes some time to adjust the added worker's labor supply after the head's displacement.

Table 1: Estimates of Wife's leisure demand on Displaced samples,
Table 2 of Stephens (2002)

Displaced Time (t)	**OLS**	**Tobit**
$t-4$	-0.0007	-0.0021
	(0.004)	(0.0058)
$t-3$	-0.0068	-0.0096
	(0.0045)	(0.0067)
$t-2$	-0.0076	-0.0092
	(0.0045)	(0.0067)
$t-1$	-0.0068	-0.0132
	(0.0047)	(0.0071)
t	-0.0073	-0.0106
	(0.0047)	(0.007)
$t+1$	-0.012	-0.02
	(0.005)	(0.007)
$t+2$	-0.015	-0.022
	(0.0053)	(0.008)
$t+3$	-0.0125	-0.017
	(0.0054)	(0.0081)
$t+4$	-0.0143	-0.021
	(0.0061)	(0.0084)

Ahn (2009) conducted similar research to Stephens (2002) in the Korean context. Ahn (2009) sought to determine the relationship between a head's unemployment and wife's labor supply using the Korean Labor & Income Panel Study (KLIPS, a representative labor market panel data of Korea) data, [6] According to Ahn (2009), a high-educated wife would work more (increase her labor supply) than a low-educated wife to compensate income loss from a husband's job loss. The magnitude of additional labor supply was also larger in the more highly-educated wife group.

On the other hand, a slightly different empirical approach was pursued by Cullen and Gruber (2000) to find added worker effect. Their main research question was 'For households in which the head become unemployed, how does Unemployment Insurance (UI) benefit crowd out a spouse's additional labor supply against income loss?' Using the Survey of Income and Program Participation (SIPP) 1984−1992 data, their main finding was that crowd out effect of the UI benefit was quite sizable. Wives of unemployed heads would work 30% more if they could not take UI benefits. From this estimation and calculation, wives would earn $73 less for each $1 of UI benefits. It is implied that in the situation of no unemployment insurance, the potential worker (i.e. wife) 's extra work on the labor market could be an adequate 'self-insurance' for supplementing household income loss caused by the head's unemployment. In contrast to previously indtroduced study Stephens (2002), Cullen and Gruber (2000)'s approach was reduced-form regression, which is not derived from the formal theoretical model.

Spletzer (1997) used Current Population Survey(CPS) data, a monthly collected panel data set from 1988 1991, in which the time gap between each individual observations is shorter than other panel data sets. The author conducted simple OLS and Probit estimation. In his estimation, the dependent variable is the wife's transitional probability of entering the labor force conditional on being a non labor force. The key independent variable is a dummy variable indicating that the head becomes unemployed. After controlling some basic demographic and educational variables, the author found a positive significant effect on the wife's probabilty of being labor force exist when the head became unemployed. However, after controling the head and wife's past economic status, the size of the estimated added worker effect declined. This

[6] Alhough I tried to do similar analysis for Korean labor market in the Great Recession time using KLIPS data, I hardly found the evidence of added-worker effect. Even if the exogenous shock to the financial market in Korea was quite big, I guessed that the shock was not spreaded to the labor market.

implies that the observed added worker effect in the descriptive statistic might be spurious, as the head's propensity of being unemployed is presumably in correlation with the wife's unobserved characteristics that affect decisions on her labor supply.

Skoufias and Parker (2006) analyzed added worker effect in a specific exogenous economic depression, Mexico Pesso Crisis of the 1990s. During the Pesso Crisis, the unemployment rate soared rapidly in the Mexican urban labor market. This study is similar to our study in that studying the causality of specific exogenous economic shocks on additional workers' labor market behavioral change. On the other hand, the empirical strategy in Skoufias and Parker (2006) is similar to that of Spletzer (1997), providing evidence from the wife's labor market status transition probability and conducting probit regression. Using the National Urban Employment Survey (Mexican panel data on the urban labor market), the authors found a significant added worker effect in the crisis. They indirectly checked correlation of labor market attrition between head and wife to avoid the heterogeneity problem driven by assortive mating suggested in Spletzer (1997). After a robustness check, they found little evidence of spurious correlation raised by heterogeneity.

Our research is basically similar to Stephens (2002), deriving an regression equation from the lifecycle labor supply model for capturing a female spouse's behavioral change in her lifecycle profile. In contrast with Stephens (2002), however, I considered borrowing constraints in the theory model. In the empirical labor economics literature, especially on estimating Intertemporal elasticity of labor supply with constant marginal utility of income (Frisch elasticity), ignoring borrowing constraints might make a downward elasticity estimator. (See Domeij and Floden (2006)) To alleviate the problem as much as possible, I have split samples which are suspected to be under borrowing constraints, to reduce variations from μ_t, a marginal utility of borrowing.

3 Data

For the empirical analysis, I used Panel Study of Income Dynamics (PSID), nationally representative panel data managed by the University of Michigan. At the first wave in 1968, the original sample of PSID was 18,0000 individuals living in 4,800 households. [7] After that, PSID has continuously followed the original sample and their split-offs since 1968, gathering labor, demographic, and educational informations. PSID consists of two sub-data sets, Survey of Economic Opportunity (SEO) sample and Survey of Research Center (SRC) sample.[8] The former is a sample selected from 1,872 low income families who lived below the poverty line in 1968, while the latter is a nationally representative sample of 2,930 families. As low income people account for a relatively large share in the datasets compared to their actual portion of the US population, using the data in the regression without considering each individual's own choice weight can creat a bias.

I have chosen biennial waves, and merged each individual and family data from 1981-2011 into a unified dataset for the analysis. As the interview interval of PSID has changed 2 years since 1997, I chose biennial waves after 1981 to maintain each wave's time gap constant. Therefore, the number of waves in this study is 16. I restrict our sample to married households with male heads' ages $20-70$. Also, I have taken observations which are continuously observed at least 3 times, to use the time lag and lead variables of the unemployment variable.

In the study, one crucial issue in making variables was how to define 'Displacement'. Following the previous studies about displacement (e.g Stevens (1997)), I defined 'Displacement' as the event of male head's involuntary (main) job loss in the previous year due to one of following reasons. [9]

1 Company folded/changed hands/moved out of town; employer died/went out of business

[7] the sample interviewed in the first wave is called core sample

[8] In the labor economics literature, the former one is often called 'Poverty Sample' and the latter one is called 'Census Sample'

[9] The question in the survey is "Why did you stop working for (NAME OF EMPLOYER)?–Did the company go out of business, were you laid off, did you quit, or what?"

2 Laid off; fired

From this definition, we can see the trends of the displacement ratio, showing how the relative size of the displaced have changed in the U.S labor market. See Table 2.

Table 2: Time Trends of Displacement Ratio

Year	Not Displaced(A)	Displaced(B)	Total(C)	Displacement ratio(B/C)
1981	2,399	66	2,465	2.677%
1983	2,662	122	2,784	**4.382%**
1985	3,026	54	3,080	1.753%
1987	3,049	50	3,099	1.613%
1989	3,078	41	3,119	1.315%
1991	3,076	54	3,130	1.725%
1993	3,007	51	3,058	1.668%
1995	3,086	33	3,119	1.058%
1997	2,724	34	2,758	1.233%
1999	2,831	42	2,873	1.462%
2001	2,974	48	3,022	1.588%
2003	3,068	64	3,132	2.043%
2005	3,211	37	3,248	1.139%
2007	3,282	49	3,331	1.471%
2009	2,962	118	3,080	**3.831%**
2011	2,710	61	2,771	2.201%
Total	47,145	924	48,069	1.922%

From Table 2, we observe that the displacement ratio in the 2009 PSID sample (reflecting labor market conditions in 2008) is the second highest in the sample period, rising quite steeply from the previous year. We can infer that the US labor market was experiencing shock from the economic recession. Thus, the spousal labor supply would be substantially different from the past as the economic environment and informations on the household's (expected) income would have changed. When I verified how long did heads who had been displaced in 2008 worked in 2010, I found that 42.7% of displaced had never worked or worked less than 20 weeks in 2010.

Table 3 is the summary statistic of observed samples in the 2009 wave, describing demographic and economic characteristicss of displaced and nondisplaced persons. In our sample, 118 male-heads have experienced 'displacement' in 2009, which makes 3.8% of the entire samples. Along with an unweighted mean and standard deviations, weighted statistics using the sample weights of 2009 are also reported.

Regarding age, both non-displaced heads and wives were about $2.7-3.7$ years older than displaced heads and wives in average. Non-displaced heads had received education about 1 year more than displaced heads. Wives of non-displaced heads had been educated 0.5 year more than those of displaced heads, reflecting the well-known theory of 'assortive mating'. Regarding ethnicity, displaced heads were more likely to be in African-American groups, corresponding to existing labor economics research that suggests ethnic minorities are more vulnerable to unexpected economic shocks in the labor market. Regarding labor income, it's not surprising that both hourly wage and annual labor earnings were much higher in non-displaced groups than displaced groups. However, the wife's labor earnings are relatively much higher in displaced groups than non-displaced groups. Even if displaced heads' annual working hours are much lower than those of non-displaced heads, we can see that wives with displaced heads work slightly more than wives with non-displaced heads. Although we can't determine causal relationship between head's displacement and wife's labor input amount or labor income, we can infer that the descriptive statisics reflect the phenomenon that displaced heads' wives increase their labor effort. Interestingly, the house mortgage gap between displaced and non-displaced groups is not that large compared to the net value of housing equity.[10] This suggests that the financial burden of a housing mortgage would be more harsh to displaced groups than non-displaced.

4 Empirical Specification

Using from the household life-cycle labor supply model, we used the baseline regression equation. More detailed theoretic background to introduce the empirical equation is written in the appendix.

[10]the net value of housing equity is defined as 'total value of housing asset in each household minus total value of mortgage principal that each household have'.

Table 3: Summary Statistic (2009)

	Unweighted		Weighted	
	Non Displaced	**Displaced**	**Non Displaced**	**Displaced**
Age (Head)	45.50	41.75	47.71	45.34
	(12.09)	(12.11)	(0.24)	(1.38)
Age (Wife)	43.64	39.90	46.01	43.66
	(11.88)	(11.79)	(0.24)	(1.42)
Education (Head)	13.51	12.51	13.76	12.78
	(2.50)	(2.30)	(0.05)	(0.28)
Education (Wife)	13.57	13.01	13.70	13.19
	(2.38)	(2.56)	(0.05)	(0.30)
# of Children ($0-13$)	0.77	1.05	0.62	0.87
	(1.06)	(1.13)	(0.02)	(0.12)
Race (Head, 1 when white)	0.74	0.65	0.87	0.81
	(0.44)	(0.48)	(0.01)	(0.04)
Race (Head, 1 when black)	0.20	0.31	0.07	0.14
	(0.40)	(0.47)	(0.00)	(0.04)
Poverty Sample	0.16	0.21	0.03	0.03
	(0.37)	(0.41)	(0.00)	(0.01)
Hourly wage (Head)	31.52	23.74	34.59	25.88
	(38.59)	(30.93)	(0.96)	(2.98)
Hourly wage (Wife)	21.92	18.22	22.99	20.59
	(18.96)	(14.06)	(0.47)	(2.53)
Work hours (Head)	2,112.65	1,670.89	2,105.88	1,638.69
	(647.36)	(811.65)	(14.74)	(88.76)
Work hours (Wife)	1,292.88	1,310.04	1,270.57	1,207.04
	(906.30)	(948.03)	(19.53)	(107.24)
Labor Earnings (Head/year)	66,023	30,626	72,631	35,659
	(95,472)	(32,507)	(2,476)	(4,427)
Labor Earnings (Wife/year)	35,554	31,527	37,924	34,648
	(36,305)	(24,168)	(966)	(3,752)
Housing Equity (Net Value)	99,152	38,966	126,161	54,815
	(201,901)	(73,770)	(5,445)	(9,722)
House Mortgage	166,180	148,628	173,441	156,226
	(143,320)	(128,214)	(4,015)	(18,529)
Observations	2,962	118	2,962	118

$$lnF_{i,t} = \alpha_i + \gamma_t \sum D_{i,t} + \beta_t \sum_{t-1}^{t+1} D_{unemp2009} + f(X_{i,t}) + \epsilon_{i,t} \quad (1)$$

The wife's leisure variable($F_{i,t}$), year dummy variables($D_{i,t}$) to control time effect, head's displacement dummy variable on 2009($D_{unemp2009}$), and other control variables($X_{i,t}$) are included in the equation. Within control variables, a wife's potential experience and its squared variable are used to proxy the wife's wage. In addition, the number of children in each household 0 and 13 are used to control the wife's utility modifier on leisure in the regression equation. The wife's potential experience is calculated following Stephens (2002) methods.[11] Each individual's time-invariant term(α_i) represents each individual's marginal utility of wealth(λ) plus the sum of inverse time-discount rate in our theoretical model. (see Apendix.) This would have a correlation with the main regressor, the displacement dummy variable. Thus, I adopted a linear fixed effect model as a bench-mark model that controls the correlation between individual time-invariant fixed term and explanatory parts, rather than using the random effect model.

In addition to using the head's displacement dummy variable which is our main interest , its lag and lead of head's displacement dummy variables are also included to identify pre- or post displacement effect on spouse's added labor supply. For example, suppose that the displacement was anticipated (warned/noticed by employer or the industry environment) sufficiently early that displaced households would have enough time to prepare for coming job loss. In such a case there might be pre-displacement effect, increasing spousal labor input earlier than the actual displacement. On the other hand, what if the economic recession was expected to last for a long time, contrary to some household's optimistic expectation that the economy would get better soon? In thie case the recession might make post-displacement effect in the labor market in

[11]

$$\text{Potential exterience} = \begin{cases} \text{Age-Education-6} \\ \text{Age-18 if wife's completed education year is less than 12} \end{cases}$$

Implementing the regression analysis, both wife's potential experience and reported hourly wage variables are used to compare their esitimates.

that spouses who didn't increase their labor supply immediately after a head's displacement would need to work more. Lag and lead variables of displacement would verify pre- and post-displacement effect on a spouse's labor supply. [12]

At first, a linear fixed effect is adopted as a benchmark estimation methods to eliminate an individual time-invariant fixed effect (α_i) in the empirical formula. Furthermore, as PSID is composed of two sub-data that each represent the whole population and the underprivileged class of U.S., the raw data itself cannot be considered as a representative random sample of the entire US population. Therefore, to get a more precise coefficient, I've estimated (1) in a Fixed-Effect sense by using individual cross-sectional weight. After eliminating the individual fixed effect by first differenciation (1), WLS with cross-sectional weight was adopted. Unfortunately, PSID changed methods of calculating individual sample weights since the 1995 wave, and it's not rationale to use different types of sample weights together in the WLS regression. Therefore, only the most recent 8 waves after 1996 are available for weighted regression analysis. Lastly, we should be careful that some parts of our dependent variable (wife's leisure) is upper-censored for some level. In our data, about 24.6 % ($\frac{11{,}285}{45{,}871}$) of whole samples were upper-censored. It's well known that linear regression on censored dependent variables would incur misleading inferences, from the fact that $E(y|x)$ can be negative linear in x. Therefore, the (Random Effect) Panel Tobit methods was applied to deal with the censored dependent variable problem. It's also crucial that when the wife's wage was observed, the dependent variable (wife's leisure time) would not be censored. Therefore, log wages of the wife were not included in the set of explanatory variables. When reporting the result of Panel Tobit estimation, coefficients are 'marginal effects at means' that all other explanatory variables are fixed on their average value. [13] [14]

[12]The number of children in each households is created by examining individual within a household every year in the merged individual data set.

[13]Implementing panel tobit estimation, random effect model was applied. Fixed effect panel tobit estimation developed by Honore (1992) would be tried in the follow-up research.

[14]White's heteroskedasticity robust estimator was used. It's well-known that White's estimator returns standard errors that are asymptotically robust to conditional heteroscedasticity and serial autocorrelations, when N is sufficiently large and t is short. Though not attached in the article, I could see smaller standard errors when I used Fixed GLS estimator (usually called 'Kiefer's arbitrary intertemporal covariance estimation') , which assumes intratempo-

5 Estimation Result

In the Estimation Results section, several estimates are presented by estimation methods and analyzed sub-samples groups. As described in the previous section, 3 empirical methods (Linear Fixed Effect, First Differencing with cross-section weight, Panel Tobit) were used. For the analysis, whole PSID household data, SRC data (Census sample), and SEO data (Poverty Sample) were used. In addition, four minority groups who are believed to be severely economically shocked after the head's displacement were selected. [15]

<Samples for Minorities>

1 (Household Income) Household with low income, less than medium level of each wave.

2 (Housing Assets) Households with negative housing asset values, whose net housing asset values are less than 0.

3 (Ethnicity) Heads are African-Americans

4 (Education) Heads are low educated, completed education level is less than 12.

Table 4: Regression results table numbers

	Unweighted Fixed Effect	Weighted First Difference	Panel Tobit
Whole Sample	Table FE-1	Table FD-1	Table Tobit-1
Census Sample (SRC)	Table FE-2	Table FD-2	Table Tobit-2
Poverty Sample (SEO)	Table FE-3	Table FD-3	Table Tobit-3
Households Income	Table FE-4	Table FD-4	Table Tobit-4
Negative Housing Asset	Table FE-5	Table FD-5	Table Tobit-5
African Americans (Head)	Table FE-6	Table FD-6	Table Tobit-6
By Education	Table FE-7	Table FD-7	Table Tobit-7

In the unweighted fixed effect model which is our basic benchmark model, signs on the coefficient of a head's displacement dummy variable were all negative yet insignificant when

ral homoscedasticity and not impose any assumptions on intertemporal correlations. See Kiefer (1980), Wooldridge (2010) for more details.

[15] In each tables, spousal's potential experience ans it squared varables are used as explanatory variables in first two colums, whereas wife's log hourly wage variable is used in latter two columns.

using the entire set of data, Census Sample data, or Poverty Sample data. Though the coefficient's magnitude (-0.031−-0.045) and statistical significance were stronger in poverty sample who are expected to be more strongly affected by the recession, its p-value is not less than 0.1. Though the poverty sample's coefficients were not statistically significant, we can guess that there was a relatively large added worker effect for the sample compared to the census sample or the whole panel data sample. When I did the same analysis for the households whose housing asset value were negative in 2008 (thus, samples who are expected to suffer from borrowing constraint in the Great Recession), the coefficient's magnitude and significance are quite larger than those in other samples. In the African-American heads group, I found similar magnitudes and significances to negative-housing wealth groups. It suggests that these two groups were minorities who more harshly suffered under economic hardship in the recession and tried to overcome their situation by securing labor income from additional worker's labor supply. Compared with Stephens (2002) who analyzed AWE in a more general context, size and significance of coefficients on displacement variable are much larger in both African-American and negative household asset samples. However, I could only find pre-displacement effect on spousal labor supply in African-American groups.

Overall, size and significances of coefficients on displacement dummies became smaller when conducting first difference weighted regression with cross-sectional choice weights. We couldn't find evidence of added worker effect when using whole sample or census sample. In the poverty sample case, however, we found slightly significant sign of AWE when using lag and lead variables. Nevertheless, it is difficult to make a rash conclusion that we found added worker effect in the poverty sample, as there was no sign of AWE when we do not take lag and lead variable of displacement dummy. When we split samples by income levels, we found small AWE in low income groups, but no significance. In the negative housing asset value sample case, the size and significance of the coefficient was similar to those of simple fixed effect cases when we didn't include lead and lag variables. Significance of AWE weakened when lead and lag variables were included. In the African-American sample, slightly significant

AWE was found in case of analysis with lag and lead variables. Though the size and significance of AWE became different depending on the inclusion of lag and lead variables, we could find the evidence of AWE in economically vulnerable groups, i.e low income groups, negative housing asset groups, and African-American groups.

In Panel Tobit analysis, maximum-likelihood estimation considering upper level censored part of dependent variable, I found similar patterns with unweighted fixed effect case. AWE was not appeared in either whole sample or census sample cases. It grew in size and significance in poverty sample cases. When I focused on economically vulnerable groups in 2008, AWE was more larger and significant than in poverty sample case. However, I couldn't find any prior or post effect of displacement except for in the African-American sample case. As the unit of time gap in the sample is 2-years –2 times longer than that of Stephens (2002)– it is much harder to observe prior or post- effect of displacement on spousal labor supply.

Table FE-1. Fixed Effect model
Whole sample & unweighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.0114	-0.00997	-0.0167*	-0.0213**
	(0.00982)	(0.0122)	(0.00939)	(0.0108)
D_unemp2009_past1		-0.0126		-0.0248**
		(0.0107)		(0.0100)
D_unemp2009_post1		0.0203		0.00727
		(0.0132)		(0.0114)
wife_poten_experience	-0.00438***	-0.00437***		
	(0.00131)	(0.00131)		
wife_poten_experience_sqd	0.000134***	0.000135***		
	(5.91e-06)	(5.91e-06)		
num_child_0to13_	0.0314***	0.0314***	0.0199***	0.0199***
	(0.000933)	(0.000933)	(0.000858)	(0.000858)
log_wife_hourlywage			0.0188***	0.0188***
			(0.00153)	(0.00153)
Year Dummy	Yes	Yes	Yes	Yes
Constant	4.978***	4.978***	4.887***	4.887***
	(0.00897)	(0.00897)	(0.00349)	(0.00349)
Observations	45,871	45,871	35,697	35,697
R-squared	0.086	0.086	0.059	0.059
Number of indiv_id	6,051	6,051	5,877	5,877

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FE-2. Fixed Effect model
Census sample & unweighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.00704	-0.00304	-0.0184*	-0.0201*
	(0.0112)	(0.0135)	(0.0110)	(0.0122)
D_unemp2009_past1		-0.00298		-0.0187*
		(0.0116)		(0.0102)
D_unemp2009_post1		0.0231*		0.0131
		(0.0139)		(0.0133)
wife_poten_experience	-0.00413**	-0.00413**		
	(0.00161)	(0.00161)		
wife_poten_experience_sqd	0.000136***	0.000136***		
	(6.79e-06)	(6.79e-06)		
num_child_0to13_	0.0353***	0.0353***	0.0226***	0.0226***
	(0.00111)	(0.00111)	(0.00101)	(0.00101)
log_wife_hourlywage			0.0163***	0.0163***
			(0.00179)	(0.00179)
Year Dummy	Yes	Yes	Yes	Yes
Constant	4.976***	4.976***	4.890***	4.890***
	(0.0102)	(0.0102)	(0.00433)	(0.00433)
Observations	33,210	33,210	26,009	26,009
R-squared	0.102	0.102	0.066	0.066
Number of indiv_id	4,078	4,078	4,018	4,018

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FE-3. Fixed Effect model
Poverty sample & unweighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.0313	-0.0453	-0.0111	-0.0269
	(0.0198)	(0.0297)	(0.0175)	(0.0234)
D_unemp2009_past1		-0.0568**		-0.0415
		(0.0255)		(0.0261)
D_unemp2009_post1		0.00143		-0.0181
		(0.0360)		(0.0200)
wife_poten_experience	-0.00500**	-0.00493**		
	(0.00223)	(0.00222)		
wife_poten_experience_sqd	0.000137***	0.000137***		
	(1.21e-05)	(1.21e-05)		
num_child_0to13_	0.0198***	0.0198***	0.0110***	0.0111***
	(0.00163)	(0.00163)	(0.00158)	(0.00158)
log_wife_hourlywage			0.0274***	0.0274***
			(0.00289)	(0.00289)
Year Dummy	Yes	Yes	Yes	Yes
Constant	4.989***	4.989***	4.880***	4.880***
	(0.0183)	(0.0182)	(0.00586)	(0.00587)
Observations	12,661	12,661	9,688	9,688
R-squared	0.053	0.053	0.053	0.053
Number of indiv_id	1,973	1,973	1,859	1,859

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FE-4. Fixed Effect model
By Income groups & unweighted

VARIABLES	(1) low income group	(2) low income group	(3) high income group	(4) high income group
D_unemp2009	-0.0150	-0.0139	0.00391	0.00556
	(0.0125)	(0.0153)	(0.0159)	(0.0186)
D_unemp2009_past1		-0.0190		0.0117
		(0.0139)		(0.0162)
D_unemp2009_post1		0.0215		-0.00203
		(0.0158)		(0.0289)
wife_poten_experience	-0.00635***	-0.00635***	-0.000488	-0.000487
	(0.00178)	(0.00178)	(0.00150)	(0.00150)
wife_poten_experience_sqd	0.000113***	0.000113***	8.50e-05***	8.50e-05***
	(7.80e-06)	(7.80e-06)	(9.44e-06)	(9.44e-06)
num_child_0to13_	0.0232***	0.0232***	0.0349***	0.0349***
	(0.00130)	(0.00130)	(0.00129)	(0.00129)
Year Dummy	Yes	Yes	Yes	Yes
Constant	5.028***	5.028***	4.913***	4.913***
	(0.0112)	(0.0111)	(0.0114)	(0.0114)
Observations	22,915	22,915	22,956	22,956
R-squared	0.055	0.055	0.094	0.094
Number of indiv_id	4,929	4,929	4,208	4,208

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FE-5. Fixed Effect model
Negative wealth households in 2009 & unweighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.0414**	-0.0384*	-0.0444**	-0.0523**
	(0.0171)	(0.0231)	(0.0178)	(0.0232)
D_unemp2009_past1		-0.00912		-0.0267
		(0.0200)		(0.0208)
D_unemp2009_post1		0.0215		0.00541
		(0.0249)		(0.0276)
wife_poten_experience	0.00102	0.00105		
	(0.00370)	(0.00368)		
wife_poten_experience_sqd	0.000136***	0.000137***		
	(1.73e-05)	(1.73e-05)		
num_child_0to13_	0.0285***	0.0285***	0.0141***	0.0142***
	(0.00249)	(0.00250)	(0.00213)	(0.00213)
Year Dummy	Yes	Yes	Yes	Yes
log_wife_hourlywage			0.0230***	0.0229***
			(0.00362)	(0.00362)
Constant	5.032***	5.032***	4.918***	4.918***
	(0.0146)	(0.0146)	(0.0117)	(0.0117)
Observations	6,589	6,589	5,237	5,237
R-squared	0.074	0.074	0.055	0.056
Number of indiv_id	1,027	1,027	1,053	1,053

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FE-6. Fixed Effect model
African Americans & unweighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.0350**	-0.0530**	-0.00449	-0.0220
	(0.0155)	(0.0229)	(0.0141)	(0.0184)
D_unemp2009_past1		-0.0577***		-0.0438**
		(0.0198)		(0.0202)
D_unemp2009_post1		-0.00712		-0.0166
		(0.0283)		(0.0179)
wife_poten_experience	-0.00475	-0.00464		
	(0.00330)	(0.00328)		
wife_poten_experience_sqd	0.000146***	0.000146***		
	(1.32e-05)	(1.33e-05)		
num_child_0to13_	0.0154***	0.0154***	0.00738***	0.00752***
	(0.00192)	(0.00192)	(0.00172)	(0.00173)
log_wife_hourlywage			0.0296***	0.0296***
			(0.00321)	(0.00321)
Year Dummy	Yes	Yes	Yes	Yes
Constant	4.987***	4.986***	4.876***	4.876***
	(0.0229)	(0.0228)	(0.00706)	(0.00706)
Observations	10,165	10,165	7,995	7,995
R-squared	0.056	0.057	0.058	0.059
Number of indiv_id	1,545	1,545	1,469	1,469

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FE-7. Fixed Effect model
By Education groups & unweighted

VARIABLES	(1) low education group	(2) low education group	(3) high education group	(4) high education group
D_unemp2009	-0.0192	-0.0239*	0.00131	0.0125
	(0.0120)	(0.0141)	(0.0163)	(0.0206)
D_unemp2009_past1		-0.0249**		0.00635
		(0.0106)		(0.0194)
D_unemp2009_post1		0.00427		0.0468**
		(0.0147)		(0.0226)
wife_poten_experience	-0.00566***	-0.00565***	-0.00274	-0.00274
	(0.00184)	(0.00184)	(0.00182)	(0.00182)
wife_poten_experience_sqd	0.000142***	0.000142***	0.000131***	0.000130***
	(7.83e-06)	(7.83e-06)	(9.37e-06)	(9.36e-06)
num_child_0to13	0.0232***	0.0232***	0.0380***	0.0380***
	(0.00135)	(0.00135)	(0.00131)	(0.00131)
Year Dummy	Yes	Yes	Yes	Yes
Constant	5.006***	5.006***	4.955***	4.955***
	(0.0164)	(0.0164)	(0.00891)	(0.00891)
Observations	23,482	23,482	22,389	22,389
R-squared	0.067	0.067	0.111	0.112
Number of indiv_id	3,422	3,422	2,893	2,893

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FD-1. First-Difference model
Whole sample & weighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.00726	0.00132	-0.0144	-0.00424
	(0.00901)	(0.0162)	(0.00998)	(0.0145)
D_unemp2009_past1		-0.00334		-0.00773
		(0.0104)		(0.00994)
D_unemp2009_post1		0.0214		0.0302
		(0.0208)		(0.0226)
wife_poten_experience	-0.00177	-0.00179		
	(0.00285)	(0.00285)		
wife_poten_experience_sqd	0.000120***	0.000120***		
	(1.77e-05)	(1.77e-05)		
num_child_0to13_0	0.0275***	0.0275***	0.0207***	0.0207***
	(0.00192)	(0.00192)	(0.00188)	(0.00189)
	(0.0386)	(0.0386)	(0.00634)	(0.00637)
log_wife_hourlywage			0.0460***	0.0459***
			(0.00343)	(0.00343)
Year Dummy	Yes	Yes	Yes	Yes
Observations	18,378	18,378	13,777	13,777
R-squared	0.021	0.021	0.096	0.097

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FD-2. First-Difference model
Census sample & weighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.00754	0.00309	-0.0154	-0.00278
	(0.00930)	(0.0166)	(0.0104)	(0.0149)
D_unemp2009_past1		-0.00143		-0.00565
		(0.0106)		(0.0101)
D_unemp2009_post1		0.0236		0.0329
		(0.0214)		(0.0234)
wife_poten_experience	-0.00140	-0.00143		
	(0.00291)	(0.00291)		
wife_poten_experience_sqd	0.000119***	0.000120***		
	(1.82e-05)	(1.82e-05)		
num_child_0to13_1	0.0278***	0.0278***	0.0211***	0.0211***
	(0.00198)	(0.00198)	(0.00194)	(0.00195)
log_wife_hourlywage			0.0455***	0.0455***
			(0.00354)	(0.00354)
Year Dummy	Yes	Yes	Yes	Yes
Observations	15,352	15,352	11,387	11,387
R-squared	0.021	0.021	0.096	0.096

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FD-3. First-Difference model
Poverty sample & weighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.000810	-0.0724*	0.0114	-0.0607
	(0.0169)	(0.0400)	(0.0161)	(0.0387)
D_unemp2009_past1		-0.0803**		-0.0814***
		(0.0316)		(0.0303)
D_unemp2009_post1		-0.0621		-0.0600
		(0.0470)		(0.0443)
wife_poten_experience	-0.0124*	-0.0122*		
	(0.00718)	(0.00715)		
wife_poten_experience_sqd	0.000147***	0.000146***		
	(5.32e-05)	(5.33e-05)		
num_child_0to13_	0.0164***	0.0164***	0.0107**	0.0109**
	(0.00546)	(0.00546)	(0.00528)	(0.00529)
log_wife_hourlywage			0.0584***	0.0584***
			(0.00851)	(0.00850)
Year Dummy	Yes	Yes	Yes	Yes
Observations	3,026	3,026	2,390	2,390
R-squared	0.019	0.021	0.113	0.116

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FD-4. First Difference model
By Income groups & weighted

VARIABLES	(1) low income group	(2) low income group	(3) high income group	(4) high income group
D_unemp2009	-0.0158	-0.00821	0.0109	0.0117
	(0.0112)	(0.0227)	(0.0146)	(0.0229)
D_unemp2009_past1		-0.00586		-0.00150
		(0.0154)		(0.0138)
D_unemp2009_post1		0.0198		0.00442
		(0.0272)		(0.0333)
wife_poten_experience	-0.00232	-0.00236	-0.00111	-0.00111
	(0.00498)	(0.00497)	(0.00336)	(0.00336)
wife_poten_experience_sqd	0.000121***	0.000122***	0.000117***	0.000117***
	(2.31e-05)	(2.31e-05)	(2.78e-05)	(2.78e-05)
num_child_0to13_	0.0270***	0.0270***	0.0273***	0.0273***
	(0.00317)	(0.00317)	(0.00232)	(0.00232)
Year Dummy	Yes	Yes	Yes	Yes
Observations	8,936	8,936	9,442	9,442
R-squared	0.024	0.024	0.021	0.021

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FD-5. First Difference model
Negative wealth households in 2009 & weighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.0446**	-0.0238	-0.0538**	-0.0279
	(0.0177)	(0.0324)	(0.0218)	(0.0318)
D_unemp2009_past1		0.0168		0.00729
		(0.0210)		(0.0220)
D_unemp2009_post1		0.0247		0.0475
		(0.0412)		(0.0506)
wife_poten_experience	0.00907	0.00901		
	(0.00705)	(0.00706)		
wife_poten_experience_sqd	0.000124**	0.000125**		
	(5.75e-05)	(5.75e-05)		
num_child_0to13_14	0.0231***	0.0230***	0.0158***	0.0155***
	(0.00503)	(0.00503)	(0.00541)	(0.00541)
log_wife_hourlywage			0.0365***	0.0366***
			(0.00787)	(0.00787)
Year Dummy	Yes	Yes	Yes	Yes
Observations	4,036	4,036	2,883	2,883
R-squared	0.021	0.022	0.069	0.069

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FD-6. First Difference model
African Americans & weighted

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure	(3) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.00422	-0.0638*	0.0368	-0.00532
	(0.0225)	(0.0350)	(0.0230)	(0.0372)
D_unemp2009_past1		-0.0421*		-0.0252
		(0.0246)		(0.0179)
D_unemp2009_post1		-0.0788*		-0.0578
		(0.0474)		(0.0465)
wife_poten_experience	-0.00368	-0.00360		
	(0.00711)	(0.00713)		
wife_poten_experience_sqd	0.000160***	0.000157***		
	(5.70e-05)	(5.69e-05)		
num_child_0to13_5	0.0214**	0.0220***	0.0189***	0.0194***
	(0.00845)	(0.00849)	(0.00670)	(0.00676)
log_wife_hourlywage			0.0451***	0.0452***
			(0.0107)	(0.0108)
Year Dummy	Yes	Yes	Yes	Yes
Observations	3,547	3,547	2,809	2,809
R-squared	0.025	0.027	0.084	0.085

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table FD-7. First Difference model
By Education & weighted

VARIABLES	(1) low education group	(2) low education group	(3) high education group	(4) high education group
D_unemp2009	-0.0168	-0.0194	0.00352	0.0293
	(0.0120)	(0.0204)	(0.0133)	(0.0252)
D_unemp2009_past1		-0.0167		0.0162
		(0.0138)		(0.0151)
D_unemp2009_post1		0.0127		0.0362
		(0.0277)		(0.0305)
wife_poten_experience	-0.00407	-0.00415	-0.000324	-0.000313
	(0.00585)	(0.00585)	(0.00240)	(0.00240)
wife_poten_experience_sqd	0.000116***	0.000116***	0.000129***	0.000129***
	(2.61e-05)	(2.61e-05)	(2.42e-05)	(2.42e-05)
num_child_0to13_	0.0220***	0.0220***	0.0310***	0.0310***
	(0.00344)	(0.00343)	(0.00222)	(0.00222)
Year Dummy	Yes	Yes	Yes	Yes
Observations	8,280	8,280	10,098	10,098
R-squared	0.014	0.014	0.028	0.028

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table Tobit-1. Panel Tobit model
Whole sample

VARIABLES	(1) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.00834	-0.00595
	(0.0116)	(0.0121)
D_unemp2009_past1		-0.0125
		(0.0119)
D_unemp2009_post1		0.0284**
		(0.0125)
wife_poten_experience	-0.00573***	-0.00573***
	(0.000235)	(0.000235)
wife_poten_experience_sqd	0.000215***	0.000215***
	(4.68e-06)	(4.68e-06)
num_child_0to13_	0.0425***	0.0425***
	(0.000730)	(0.000730)
Year Dummy	Yes	Yes
Constant	4.998***	4.998***
	(0.00342)	(0.00342)
Observations	45,871	45,871
Number of indiv_id	6,051	6,051
Uncensored Observations	34,586	34,586
Censored Observations	11,285	11,285

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table Tobit-2. Panel Tobit model
Census sample

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure
D_unemp2009	-0.00250	0.00191
	(0.0130)	(0.0134)
D_unemp2009_past1		-0.00175
		(0.0132)
D_unemp2009_post1		0.0301**
		(0.0139)
wife_poten_experience	-0.00572***	-0.00572***
	(0.000265)	(0.000265)
wife_poten_experience_sqd	0.000214***	0.000214***
	(5.24e-06)	(5.24e-06)
num_child_0to13_	0.0472***	0.0472***
	(0.000844)	(0.000844)
Year Dummy	Yes	Yes
Constant	4.997***	4.997***
	(0.00411)	(0.00411)
Observations	33,210	33,210
Number of indiv_id	4,078	4,078
Uncensored Observations	25,182	25,182
Censored Observations	8,028	8,028

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table Tobit-3. Panel Tobit model
Poverty sample

VARIABLES	(1) log_wife_leisure	(4) log_wife_leisure
D_unemp2009	-0.0341	-0.0433
	(0.0262)	(0.0276)
D_unemp2009_past1		-0.0582**
		(0.0273)
D_unemp2009_post1		0.0147
		(0.0281)
wife_poten_experience	-0.00629***	-0.00629***
	(0.000510)	(0.000510)
wife_poten_experience_sqd	0.000228***	0.000228***
	(1.05e-05)	(1.05e-05)
num_child_0to13_	0.0289***	0.0289***
	(0.00146)	(0.00146)
Year Dummy	Yes	Yes
Constant	5.009***	5.009***
	(0.00636)	(0.00635)
Observations	12,661	12,661
Number of indiv_id	1,973	1,973
Uncensored Observations	9,404	9,404
Censored Observations	3,257	3,257

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table Tobit-4. Panel Tobit model
By income Groups (Low Income Groups)

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure
D_unemp2009	-0.0155	-0.0152
	(0.0158)	(0.0165)
D_unemp2009_past1		-0.0240
		(0.0163)
D_unemp2009_post1		0.0251
		(0.0160)
wife_poten_experience	-0.00516***	-0.00517***
	(0.000354)	(0.000354)
wife_poten_experience_sqd	0.000207***	0.000208***
	(7.25e-06)	(7.25e-06)
num_child_0to13_	0.0377***	0.0376***
	(0.00116)	(0.00116)
Year Dummy	Yes	Yes
Constant	5.031***	5.031***
	(0.00510)	(0.00510)
Observations	22,915	22,915
Number of indiv_id	4,929	4,929
Uncensored Observables	15,348	15,348
Censored Observables	7,567	7,567

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table Tobit-5. Panel Tobit model
Negative wealth households in 2009

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure
D_unemp2009	-0.0429**	-0.0347
	(0.0203)	(0.0215)
D_unemp2009_past1		0.00341
		(0.0213)
D_unemp2009_post1		0.0413*
		(0.0231)
wife_poten_experience	-0.00620***	-0.00619***
	(0.000683)	(0.000682)
wife_poten_experience_sqd	0.000205***	0.000205***
	(1.50e-05)	(1.50e-05)
num_child_0to13_	0.0410***	0.0408***
	(0.00204)	(0.00204)
Year Dummy	Yes	Yes
Constant	5.051***	5.051***
	(0.0130)	(0.0130)
Observations	6,589	6,589
Number of indiv_id	1,027	1,027
Uncensored Observations	4,913	4,913
Censored Observations	1,676	1,676

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table Tobit-6. Panel Tobit model
African Americans

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure
D_unemp2009	-0.0395*	-0.0509**
	(0.0208)	(0.0220)
D_unemp2009_past1		-0.0546**
		(0.0219)
D_unemp2009_post1		0.00475
		(0.0229)
wife_poten_experience	-0.00682***	-0.00683***
	(0.000538)	(0.000538)
wife_poten_experience_sqd	0.000239***	0.000239***
	(1.08e-05)	(1.08e-05)
num_child_0to13_	0.0228***	0.0228***
	(0.00156)	(0.00155)
Year Dummy	Yes	Yes
Constant	5.014***	5.014***
	(0.00730)	(0.00730)
Observations	10,165	10,165
Number of indiv_id	1,545	1,545
Uncensored Observations	7,690	7,690
Censored Observations	2,475	2,475

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table Tobit-7. Panel Tobit model
By Education (Low Educated)

VARIABLES	(1) log_wife_leisure	(2) log_wife_leisure
D_unemp2009	-0.0196	-0.0217
	(0.0158)	(0.0164)
D_unemp2009_past1		-0.0233
		(0.0162)
D_unemp2009_post1		0.0132
		(0.0170)
wife_poten_experience	-0.00701***	-0.00702***
	(0.000347)	(0.000347)
wife_poten_experience_sqd	0.000239***	0.000239***
	(6.73e-06)	(6.73e-06)
num_child_0to13_	0.0340***	0.0340***
	(0.00112)	(0.00112)
Constant	5.028***	5.028***
	(0.00503)	(0.00503)
Year Dummy	Yes	Yes
Observations	23,482	23,482
Number of indiv_id	3,422	3,422
Uncensored Observations	16,723	16,723
Censored Observations	6,759	6,759

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6 Conclusion, Limitations, and Further Researches.

In the study, I investigated whether secondary workers (female wife) in the family who are already working would increase their labor supply to smooth household consumption, when the primary worker (male head) in the family lost their jobs unexpectedly due to the Great Recession. An Equation for empirical analysis was derived from the life-cycle family labor supply model. Conducting analysis, three panel data estimation methods (Linear Fixed Effects model, First-Differencing with cross-section weights model, Panel Tobit model) were adopted. To perform empirical analysis, in addition to using PSID whole/census/poverty samples, and minorities of ethnicity, income, housing asset, and education samples were used. The results of the analysis supported the theoretical conjecture of added worker effect in all models. Moreover, size and significance of coefficients were larger in minority samples of ethnicity and housing asset. Compared to Stephens (2002), who analyzed AWE in a more general situation, size and significance of our study's AWE coefficients were much larger.

Some points should be stated as limitations of the study. First, to derive an empirical equation from the model, I have used first-order Taylor approximation methods to transform an equation about lagrangian multiplier on household's budget constraint ($lambda_t$)into a linearized formula. (see appendix.) Therefore, there might be an 'omitted variable bias' problem, as approximation errors higher than second order terms are neglected.

Also, I have tried to see 'crowd-out effects of Unemployment Insurance(UI)'. According to Cullen and Gruber (2000), AWE were diminished for households who had received unemployment insurance, as UI 'crowd out' incentives for secondary workers were greater. However, it was difficult to perform analysis on 'crowd-out effects', as few families had received UI in my sample data.

Lastly, prior and post dummy variable of one's displacement were included in the estimation to see the effects of anticipating one's job displacement or the effects of unemployment's long-term persistence. However, those effects were imprecise as time gap between observations were in 2 years intervals.

Two methods of follow-up research or extensions can be conducted. First is extension about empirical analysis. For specific industries, we can see in which industry sectors finding new employment would be least difficult when a worker is displaced. Furthermore, we can verify how the size of AWE would changed for each kinds of industries.

Another method is the dynamic macroeconomic approach. In the dynamic macroeconomic model considering household labor supply decision, we can simulate whether secondary workers in households would increase their labor supply when a family suffered from exogenous economic shock. Furthermore, welfare changes from AWE can be also measured. In this case, as the distribution of each family's income and wealth are generated that are similar to the real world economy, the heterogeneous agent model should be adopted. [16]

[16] In the heterogeneous agent model of macroeconomics, Pijoan-Mas (2006) conducted simulation analysis between precautaionary savings and additional work, when heterogeneous households in the model economy were shocked. Following Pijoan-Mas (2006), Ortigueira and Siassi (2013) did household labor supply analysis in the heterogeneous agent economy context when the capital market is incomplete.

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A Appendix : Model

In appendix, we'll discuss how to derive labour-supply equation used in the study. The basic methods for deriving labor supply regression equation from the life-cycle model is introduced in MaCurdy (1981), and applied in Stephens (2002) and Ahn (2009). In addition to the basic model, the labor supply esimation problem in the life-cycle model framework with considering borrowing constraint is introduced in Domeij and Floden (2006) and Keane and Rogerson (2012). Subscript i, which indicates each households, is omitted for simplicity.

The table below is the summary of notations used in appendix.

Table 5: Notations in appendix

Notation	Explanation
C_t	Household's consumption at t
M_t	Head's leisure at t
F_t	Wife's leisure at t
A_t	Household's physical asset at t
A_{C_t}	utility modifier of C at t
A_{M_t}	utility modifier of M at t
A_{F_t}	utility modifier of F at t
β	time discount rate
$\bar{L}$	Total time for individuals in each period
r_t	one-period time constant real interest rate
λ_t	Marginal utility of wealth for each households
μ_t	Marginal utility of borrowing constraint

Consider the problem of maximizing the household utility function, which is intratemporal seperable between head and wife's leisure.

$$\max_{\{C_t, M_t, F_t, A_{t+1}\}} U_t = E_t[\sum_{t=0}^{T} \beta^t \left\{ A_{C_t}(C_t)^\sigma + A_{M_t}(M_t)^\psi + A_{F_t}(F_t)^\phi \right\}] \tag{2}$$

subject to the household intertemporal budget constraint.

$$\begin{aligned} A_{t+1} &= (1+r_t)A_t + w_{m,t}(\bar{L}-M_t) + w_{f,t}(\bar{L}-F_t) - C_t \\ A_T &= 0 \text{ (Terminal Condition)} \\ A_{t+1} &\geq 0 \text{ (Borrowing Constraint)} \end{aligned} \tag{3}$$

By using Lagrangean Methods,

$$\begin{aligned} \mathcal{L} = \quad & E_t[\sum_{t=0}^{T} \beta^t \left\{ A_{C_t}(C_t)^{\sigma} + A_{M_t}(M_t)^{\psi} + A_{F_t}(F_t)^{\phi} \right\} \\ & + \lambda_t \left\{ (1+r_t)A_t + w_{m,t}(\bar{L}-M_t) + w_{f,t}(\bar{L}-F_t) - C_t - A_{t+1} \right\} \\ & + \mu_t A_{t+1}] \end{aligned} \tag{4}$$

Then, from the household's dynamic optimization on choice variables in t, We get the First-order conditions like

$$C_t)\ A_{C_t}\sigma C_t^{\sigma-1} = \lambda_t \tag{5}$$

$$M_t)\ A_{M_t}\psi M_t^{\psi-1} \geq \lambda_t w_{m,t} \tag{6}$$

$$F_t)\ A_{F_t}\phi F_t^{\phi-1} \geq \lambda_t w_{f,t} \tag{7}$$

$$A_{t+1})\ \lambda_t - \mu_t = E_t[\beta(1+r_t)(\lambda_{t+1})] \tag{8}$$

$$\lambda_t) \text{ Intertemporal Budget Constraint} \tag{9}$$

$$\mu_t) \text{ Borrowing Constraint} \tag{10}$$

If the borrowing constraint were binding, its lagrangean multiplier would be strictly positive. ($\mu_t > 0$). Like Lee (2000), we can rewrite (8) by assuming that there exists an asset offering a risk-free real rate of interest.

$$\lambda_t - \mu_t = \beta(1+r)E_t(\lambda_{t+1}) \tag{11}$$

take log on (7) for interior solution

$$\ln A_{F_t} + \ln \phi + (\phi - 1)\ln F_t = \ln \lambda_t + \ln w_{f,t}$$
$$(1-\phi)\ln F_t = \ln A_{F,t} + \ln \phi - \ln \lambda_t - \ln w_{f,t}$$

Thus,

$$\ln F_t = \frac{1}{1-\phi}\ln A_{F,t} - \frac{1}{1-\phi}\ln w_{f,t} + \frac{1}{1-\phi}(\ln \phi - \ln \lambda_t) \tag{12}$$

Then, let's transform $\ln \lambda_t$ for another expression to get an empirical equation.

Now, decompose λ_{t+1} into two terms, expected term in t and its prediction error. Assume that two terms are orghogonal.

$$\lambda_{t+1} = E_t[\lambda_{t+1}] + \epsilon_{t+1} \tag{13}$$

Using both (8) and (13), we can write

$$\lambda_t - \mu_t = \beta(1+r)E_t[\lambda_{t+1}] = \beta(1+r)(\lambda_{t+1} - \epsilon_{t+1}) \tag{14}$$

take log on (14)

$$\ln(\lambda_t - \mu_t) = \ln \beta(1+r) + \ln(\lambda_{t+1} - \epsilon_{t+1}) \tag{15}$$

By linear approximation on both sides of (15) respectively and substituting λ_t recursively, we can rewrite it as [17]

[17] Similar methods were applied in Domeij and Floden (2006). approximation errors are neglected

$$(LHS \text{ on } (15)) : \ln(\lambda_t - \mu_t) \approx \ln \lambda_t - \frac{\mu_t}{\lambda_t} + (-\frac{\mu_t}{\lambda_t})^2 + error_1$$
$$(RHS \text{ on } (15)) : \ln(\lambda_{t+1} - \epsilon_{t+1}) \approx \ln \lambda_{t+1} + \frac{\epsilon_{t+1}}{\lambda_{t+1}} + \frac{1}{2}(-\frac{\epsilon_{t+1}}{\lambda_{t+1}})^2 + error_2$$

$$\begin{aligned}
\ln \lambda_{t+1} &\approx \ln \lambda_t - \frac{\mu_t}{\lambda_t} + \ln \frac{1}{\beta(1+r)} + \frac{\epsilon_{t+1}}{\lambda_{t+1}} - \frac{1}{2}(\frac{\epsilon_{t+1}}{\lambda_{t+1}})^2 \\
&= \text{...(Substitute recursively)} \\
&= \ln \lambda_0 - \sum \frac{\mu_t}{\lambda_t} + \sum \ln \frac{1}{\beta(1+r)} + \sum \frac{\epsilon_{t+1}}{\lambda_{t+1}} - \frac{1}{2} \sum (\frac{\epsilon_{t+1}}{\lambda_{t+1}})^2
\end{aligned} \tag{16}$$

Put (16) into (12), we can get an equation that is used in the empirical analysis on F_t.

$$\begin{aligned}
\ln F_t &= \frac{1}{1-\phi} \ln A_{F,t} - \frac{1}{1-\phi} \ln w_{F,t} - \\
&\left\{ \underbrace{(\ln \lambda_0 + \sum \ln \frac{1}{\beta(1+r)})}_{\text{individual fixed effect}} + \sum \frac{\mu_t}{\lambda_t} + \gamma Dummy_{Displacement} + \sum \frac{\epsilon_{t+1}}{\lambda_{t+1}} \right\}
\end{aligned} \tag{17}$$

Equation (17) is equivalent to the equation (1) stated in the body text. Following the literature, we've used potential experience and its squared variable as proxy variables of wife's hourly wage ($w_{F,t}$). Also, wife's utility modifier on leisure ($A_{F,t}$), is considered as a function of the number of children in each house unit. Time dummies are used to control all time effects.

As μ_t, marginal utility of borrowing constraint, is not observable and probably correlated to displacement dummy variable, our main interest regression coefficient γ might be misleading unless we consider 'omitted variable bias'. To deal with the problem, we've split the sample that are severely constrained in borrowing liquidity. We expect that splitting the sample that are under economic difficulty would reduce the variation of μ_t.

국문초록

대불황 시기 미국 노동시장에서의 부가노동자효과에 대한 실증 분석

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본 논문은 2008~2009년 미국발 금융위기로 인한 소위 '대불황'시기 미국 노동시장에서의 부가노동자효과를 규명한 노동경제학 실증 분석 연구이다. 2008년 대불황은 개별 가구 입장에서 예측치 못한 외생적인 경제적 충격을 가져왔으며, 금융시장으로부터 시작해 실물 시장에까지 악영향을 미친 대규모의 경제적 사건이었다. 따라서 이 시기 미국 노동시장은 가구가 큰 규모의 외생적 소득 충격을 겪을 때 노동공급의 측면에서 어떻게 반응할 것인지를 규명하기에 적합하다.

본 연구에서는 대불황이 남성 가구주의 예측하지 못한 실직을 불러올 때 배우자가 그로 인한 소득손실충격을 (생애주기에 걸친 소비평탄화의 관점에서) 보전하기 위해 추가적으로 노동공급량을 늘리는지에 관해 규명하였다. 이를 위해 가구의 생애주기 노동공급모형을 풀어 데이터 상에서 추정 가능한 식을 도출하였으며, 이를 미국의 대표적인 패널 데이터인 PSID에 적용해 추정하였다. 패널데이터에 대한 세 가지의 서로 다른 추정방식을 적용한 결과, 모든 샘플에서 부가노동자효과를 지지하는 방향의 계수를 얻을 수 있었다. 전체 샘플에서 얻은 계수의 크기는 선행연구에서의 것과 유사했으나, 지난 대불황 시기 경제적 충격을 더욱 심하게 겪었던 그룹들 중 인종과 주택 자산으로 분류한 샘플에서 부가노동자효과를 나타내는 계수의 크기와 유의성은 보다 일반적인 상황에서 부가노동자효과를 규명한 선행연구에서보다 더욱 커 주당 0.037-0.048시간만큼 배우자의 여가 소비량을 감소시킨 것으로 나타났다. 이를 통해 우리는 대공황 시기 이들 그룹에서의 배우자들이 가구주의 실직으로 인한 소득 손실을 보전하기 위해 노동공급을 더 늘려야 했던 것을 알 수 있다.

주요단어 : 부가노동자효과, 미국 대불황시기 노동시장, PSID, 배우자 노동공급
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